

# Forecasting The Exchange Rate Between Euro And USD: Probabilistic Approach Versus ARIMA And Exponential Smoothing Techniques

Paraschos Maniatis, Athens University of Economics and Business, Greece & Kuwait-Maastricht Business School, Kuwait

## ABSTRACT

*This study attempts to model the exchange rate between Euro and USD using univariate models-in particular ARIMA and exponential smoothing techniques. The time series analysis reveals non stationarity in data and, therefore, the models fail to give reliable predictions. However, differencing the initial time series the resulting series shows strong resemblance to white noise. The analysis of this series advocates independence in data and distribution satisfactorily close to Laplace distribution. The application of Laplace distribution offers reliable probabilities in forecasting changes in the exchange rate.*

**Keywords:** Unit Roots; Random Walk; ARIMA Models; Exponential Smoothing Models; Laplace Probability Density Function

## INTRODUCTION

Forecasts in exchange rates are important for future contracts, for the imports and exports, the debt and payments of a country, the speculation on currencies... for all aspects of the international economic relations. Up to present stage of international exchanges, the efforts to stabilizing the exchange rates between the principal currencies were only partially effective, succeeding only in avoiding perverse, sudden changes of the exchange rates. Several efforts have been attempted to relate the exchange rates with the fundamentals of the economies involved, e.g. Purchasing Power Parity theories have not resulted to to forecast accurate enough for practical reasons. Besides, the problem is not only the accuracy of the forecast: as in almost all fields in economics the forecast is attempted not expecting fulfillment of the forecast but take measures of avoiding its realization. Further, due to the social character of the economic forecasts, a 'bad' forecast, from the technical point of view, can be realized, because it only worked as a self fulfilled prophecy... However, a good short-term forecast is important for mainly speculative purposes.

In this study are attempted forecasts using autoregressive schemes and exponential smoothing models. The inadequate results obtained by these models limited the effort to simply calculate probabilities for short-run changes of the exchange rate to lay in specific ranges.

## DATA AND METHODOLOGY

The data consists of 3202 daily observations of ER ranging from January 4, 1999 to July 1, 2011. The Data is shown in table 12 in the appendix to this text. The variables involved in the study are the exchange rate between Euro and USD (denoted ER), the number of observations (denoted OBS) and the differed series ER (denoted DER).

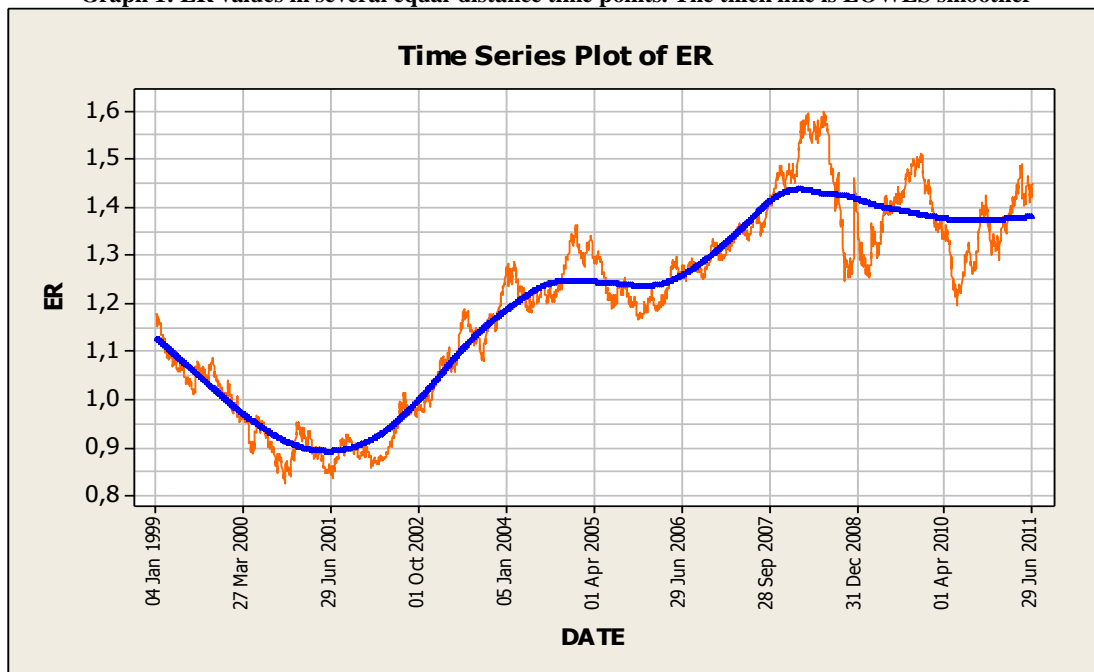
The data is first subjected to descriptive statistic analysis for identification of the characteristics of the ER series. Then it is tested the stationarity of the time series by applying the Augmented Dickey Fuller (ADF) test for existence of unit root. The non rejection of the unit root hypothesis made suspicious for forecasts the use of the

AR(1) model. Indeed, its employment resulted to very broad confidence intervals, yielding trivial forecasts. The failure of AR(1) model called for use of some alternative models, such as model belonging to the family of exponential smoothing models, which eventually yielded no better results. As last resort was the differencing of the ER series and the study of the distribution of the first differences. The study revealed a satisfactory approximation of the distribution by the Laplace distribution. Based on this result the study gives graphs and tables for the probability for the DER to lay in specific intervals.

## DESCRIPTIVES OF VARIABLE ER

Graph 1 shows the evolution of the exchange rate over the whole period of the existence of the exchange rate. The graph trend clearly indicates three phases of evolution: devaluation of Euro from start 1999, date of Euro birth, up mid 2001; then revaluation expanding up to first quarter 2008 and then a volatile and cyclical movement of the exchange rate but fluctuating at a constant level up to end June 2011.

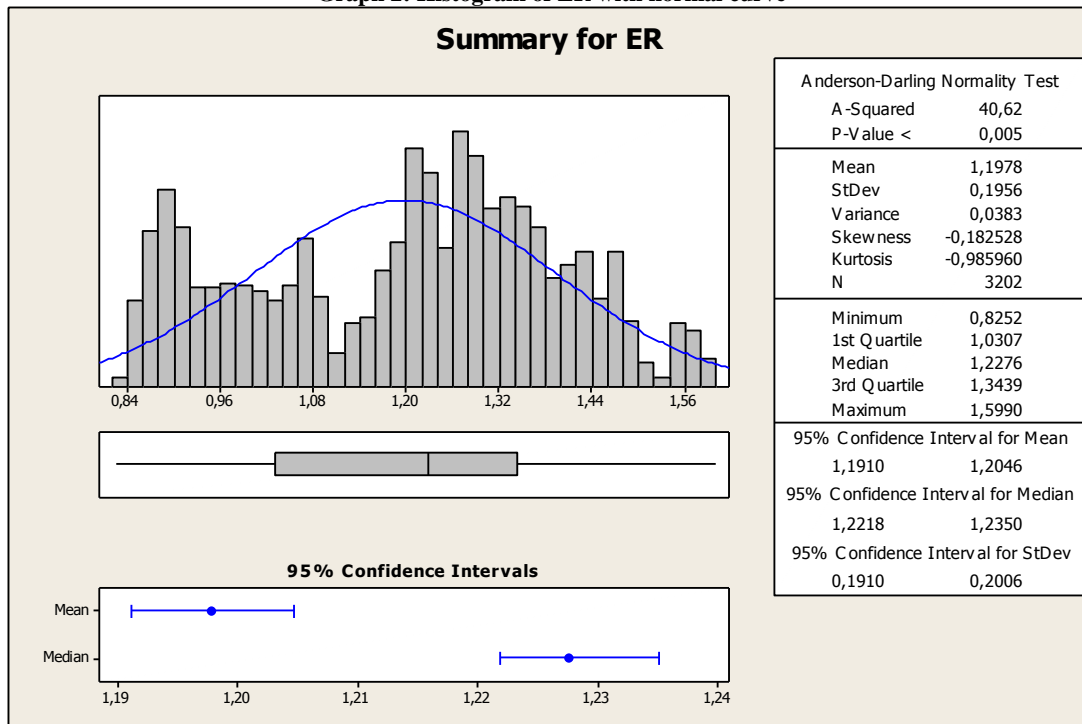
**Graph 1: ER values in several equal-distance time points. The thick line is LOWES smoother**



Source of data: European Central Bank Statistical Warehouse

The irregularities in the ER are reflected in histogram of data in graph 2, which indicates high deviation from normality, bimodal distribution with high concentration of frequencies in the ranges (0,88 ; 0,90] and (1,20 ; 1,30]. The mean ER is 1, 1978 and the median is 1, 2276.

Graph 2: Histogram of ER with normal curve



The runs test for ER rejects independence of the values in the series, with p-value 0, observed number of runs 36 and expected (in case of independence) 1564.

Table 1: Runs test for ER

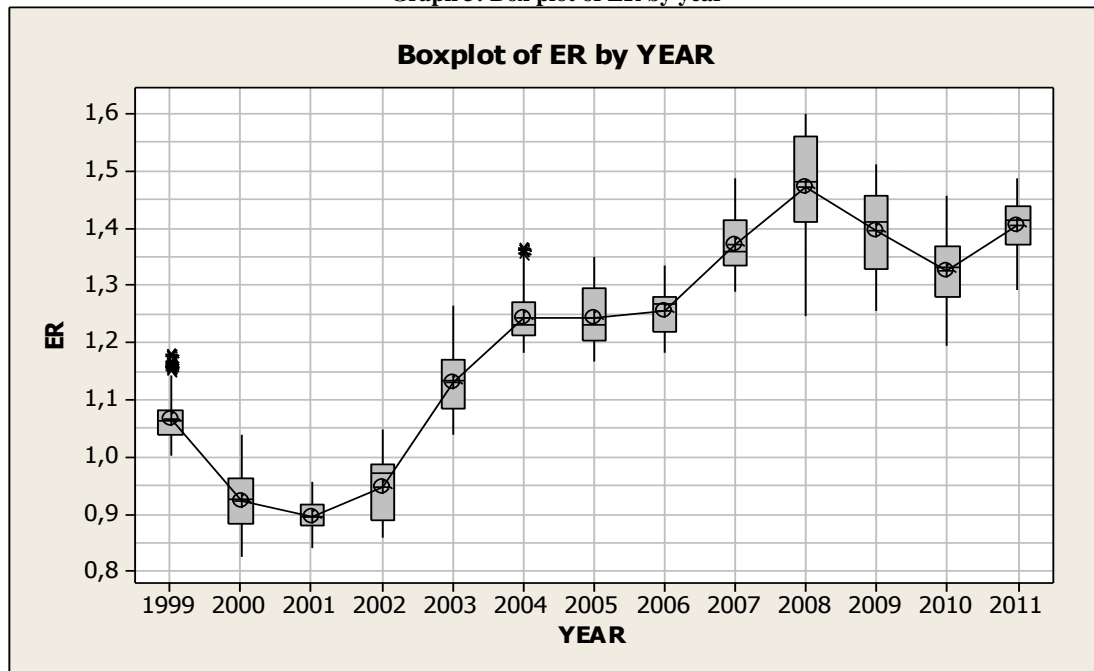
Runs test for ER  
 Runs above and below  $K = 1, 19783$   
 The observed number of runs = 36  
 The expected number of runs = 1564, 81  
 1845 observations above  $K$ ; 1357 below  
 P-value = 0,000

## TESTING FOR UNIT ROOT

### Preliminary results

Attempting forecasting with ARIMA techniques the first step is to check stationarity in the series. As preliminary step is checking if the series is- at least- time stationary, an absolute precondition for stationarity in the series. To this purpose the data is split into 13 groups, according to the year each value belongs. The box plot in graph 3 already discards possibility of time equality in means, the graph of which follows year by year the course of the initial series.

Graph 3: Box plot of ER by year



For enforcement of the hypothesis of non equality in means the groups are subjected to ANOVA analysis, the results of which are shown in table 2. In same table are shown the annual means, the standard deviations and the number of observations in each year.

Table 2: One-way ANOVA of ER versus YEAR

Source	DF	SS	MS	F	P
YEAR	12	112,4380	9,3698	2961,33	0,000
Error	3189	10,0902	0,0032		
Total	3201	122,5282			

S = 0,05625 R-Sq = 91,77% R-Sq(adj) = 91,73%

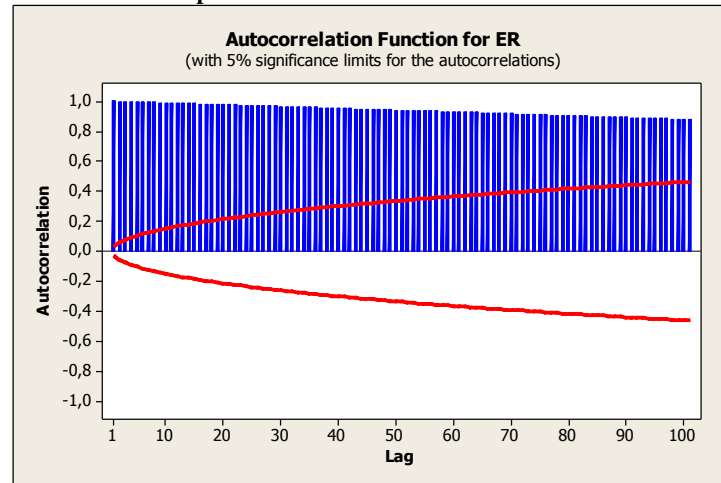
Individual 95% CIs For Mean Based on Pooled StDev

Level	N	Mean	StDev	
1999	259	1,0658	0,0402	*)
2000	255	0,9236	0,0503	(*)
2001	254	0,8956	0,0266	(*)
2002	255	0,9456	0,0531	*
2003	255	1,1312	0,0500	*)
2004	259	1,2439	0,0432	(*)
2005	257	1,2441	0,0506	(*)
2006	255	1,2556	0,0380	(*)
2007	255	1,3705	0,0534	*)
2008	256	1,4708	0,1034	*)
2009	256	1,3948	0,0731	*
2010	258	1,3257	0,0601	*)
2011	128	1,4036	0,0448	(*)

Pooled StDev = 0,0562

The p-value (zero) of Fisher's F and the high value of the adjusted coefficient of determination (91, 73%) clearly reject the hypothesis of means equality and, consequently, stationarity in the series. The above conclusion is enforced by the autocorrelation function for ER, which is typical for a non stationary time series

**Graph 4: Autocorrelation function for ER**



### FORMAL TEST FOR EXISTENCE OF UNIT ROOT

Although all the preliminary tests rejected stationarity in the ER series, it is necessary to subject the series to the augmented Dickey-Fuller (ADF) test, which is exactly tailored for identification of unit root(s) in a time series. For this purpose it is first considered the model with intercept and trend:

$$DER_t = \text{constant} + \beta * ER_{t-1} + \gamma * t + U_t \quad (t: \text{OBS}=1, 2, \dots, n) \quad (1)$$

The results of the OLS regression are shown in table 3.

**Table 3: Regression Analysis: DER versus ER; OBS**

The regression equation is					
DER = 0,00349 - 0,00398 ER + 0,000001 OBS					
Predictor	Coef	SE Coef	T	P	
Constant	0,003490	0,001273	2,74	0,006	
ER	-0,003975	0,001361	-2,92	0,004	
OBS	0,00000085	0,00000029	2,94	0,003	
S = 0,00805594 R-Sq = 0,3% R-Sq(adj) = 0,2%					
Analysis of Variance					
Source	DF	SS	MS	F	P
Regression	2	0,00060385	0,00030192	4,65	0,010
Residual Error	3198	0,20754427	0,00006490		
Total	3200	0,20814811			
Source	DF	Seq SS			
ER	1	0,00004322			
OBS	1	0,00056063			

The significance of the parameters estimates are shown in Table 4.

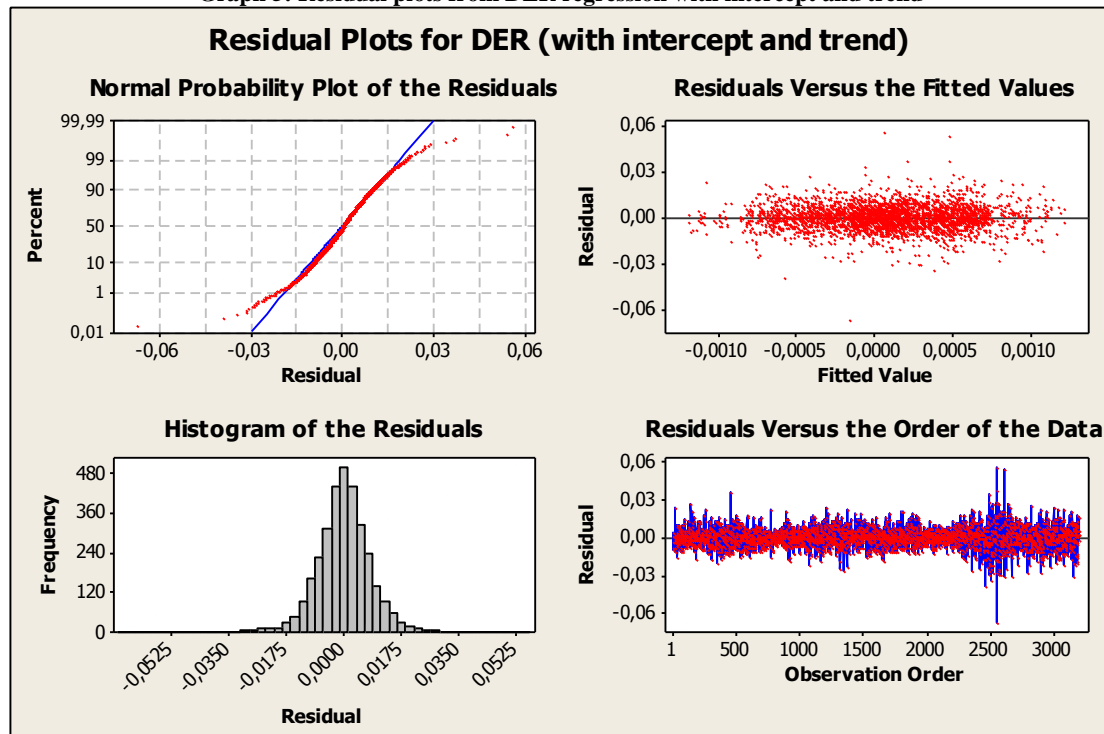
**Table 4: Significance of the parameters estimates of model  $DER_t = \text{constant} + \beta * ER_{t-1} + \gamma * t + U_t$**

Parameter	t-value	Right hand critical t-value	$H_0$ : Existence of unit root
constant	2,74	-3,66	Not rejected
$\beta$	-2,92	-3,66	Not rejected
$\gamma$	2,94	-3,66	Not rejected
All parameters simultaneously	F-value	Critical F-value	$H_0$ : Existence of unit root
	4,65	6,25	Not rejected

Source of critical values: W.A. Fuller, *Introduction to Statistical Time Series*, Wiley, New York, 1976; D.A. Dickey and W.A. Fuller, "Likelihood Ratio Statistics for Autoregressive Time Series with a unit root". *Econometrica* **49** (1981), pp. 1057-1072

Some plots of the residuals analysis from the regression are shown in Graph 5. The residuals suggest white noise, not normally distributed.

**Graph 5: Residual plots from DER regression with intercept and trend**



The second step is to consider the model (1) with constant, without trend

$$DER_t = \text{constant} + \beta * ER_{t-1} + U_t \quad (t: \text{OBS}=1, 2, \dots, n) \quad (2)$$

The results of the OLS regression are shown in table 5.

Table 5: Regression Analysis: DER versus ER

The regression equation is DER = 0,000796 - 0,000594 ER					
Predictor	Coef	SE Coef	T	P	
Constant	0,0007958	0,0008845	0,90	0,368	
ER	-0,0005940	0,0007288	-0,82	0,415	
S = 0,00806555 R-Sq = 0,0% R-Sq(adj) = 0,0%					
Analysis of Variance					
Source	DF	SS	MS	F	P
Regression	1	0,00004322	0,00004322	0,66	0,415
Residual Error	3199	0,20810490	0,00006505		
Total	3200	0,20814811			

The significance of the parameters estimates is shown in table 6.

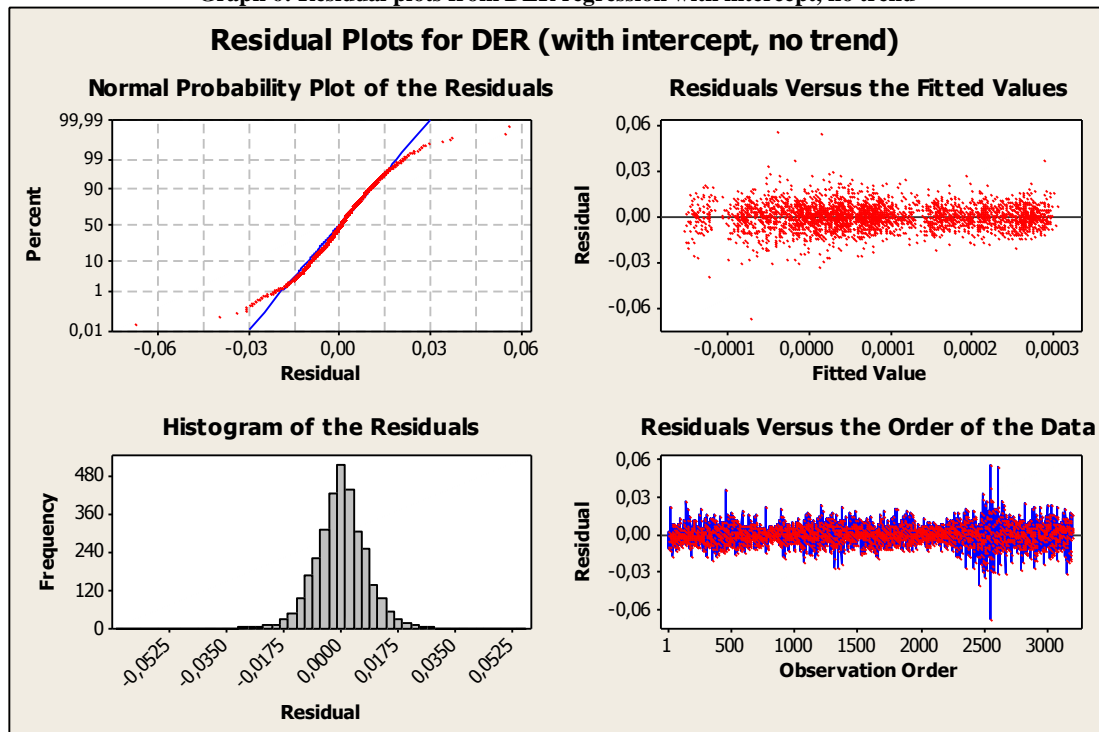
Table 6: Significance of the parameters estimates of model  $DER_t = \text{constant} + \beta \cdot ER_{t-1} + U_t$ 

Parameter	t-value	Right hand critical t-value	H <sub>0</sub> : Existence of unit root
constant	0,90	-3,12	Not rejected
$\beta$	-0,82	-3,12	Not rejected
All parameters simultaneously	F-value	Critical F-value	H <sub>0</sub> : Existence of unit root
	0,66	6,25	Not rejected

Source of critical values: W.A. Fuller, *Introduction to Statistical Time Series*, Wiley, New York, 1976; D.A. Dickey and W.A. Fuller, "Likelihood Ratio Statistics for Autoregressive Time Series with a unit root". *Econometrica* 49 (1981), pp. 1057-1072

Some plots of the residuals analysis from the regression are shown in Graph 6. The residuals suggest white noise, not normally distributed.

Graph 6: Residual plots from DER regression with intercept, no trend



The ADF test for unit root fails to reject the hypothesis of existence of unit root in the ER series. Indeed, the fitting in the ER series the autoregressive model AR(1)

$$ER_t = \text{constant} + \alpha * EP_{t-1} + U_t \quad (t=2, 3, \dots, n) \quad (3)$$

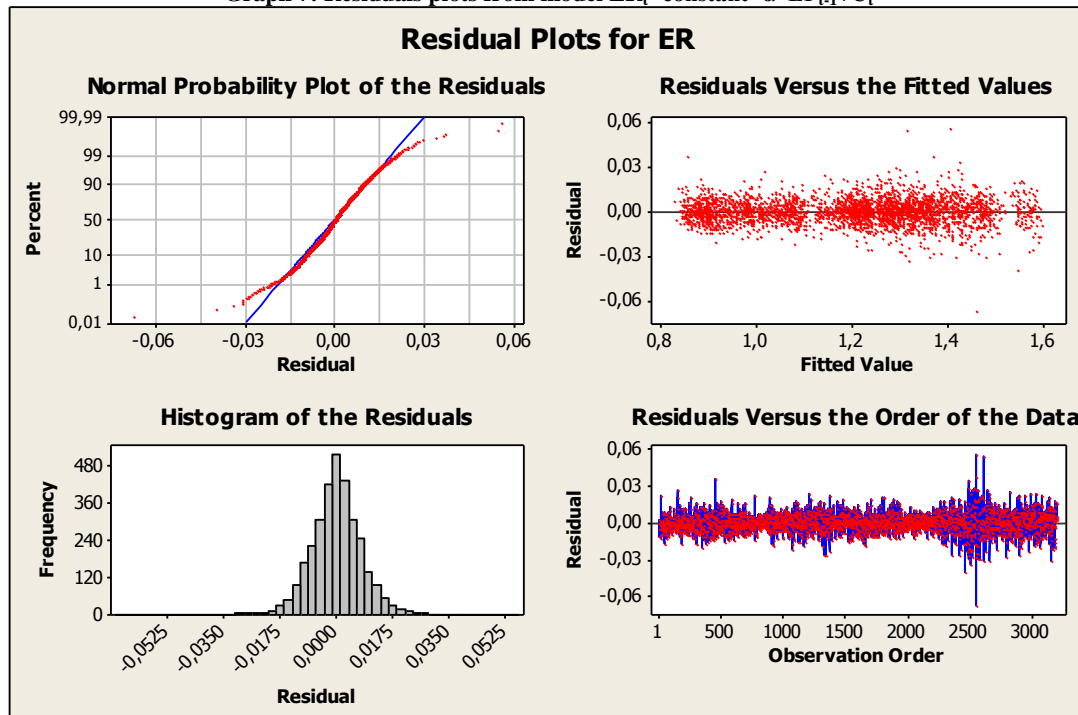
The results of the parameters estimates are as in table 7

**Table 7: ARIMA Model  $ER_t = \text{constant} + \alpha * EP_{t-1} + U_t$**

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
AR 1	0,9994	0,0007	1371,47	0,000
Constant	0,0007762	0,0001693	4,59	0,000
Mean	1,3230	0,2885		
Number of observations: 3202				
Residuals: SS = 0,208105 (backforecasts excluded)				
MS = 0,000065 DF = 3200				
Modified Box-Pierce (Ljung-Box) Chi-Square statistic				
Lag	12	24	36	48
Chi-Square	27,1	37,3	49,8	61,8
DF	10	22	34	46
P-Value	0,002	0,022	0,040	0,060

The value of the coefficient in the model is very closed to unit ( $\alpha=0,994$ ), thus enforcing the hypothesis of existence of unit root in the ER time series. The residuals plots for ER in the AR(1) scheme as shown in graph 7 is very similar to the ones obtained in the regression models (1) and (2): white noise, confirming the existence of unit root in the data.

**Graph 7: Residuals plots from model  $ER_t = \text{constant} + \alpha * EP_{t-1} + U_t$**





Although the non stationarity hypothesis in the series is supported by all the previous tests, it is worth questioning if omitting a part of the series the remaining one could eventually exhibit stationarity so that help as basis for forecasting reasons. For this purpose the series is split into two parts of equal size, each part containing 1601 observations, denoted by ER1 and ER2 respectively. On each of the so obtained series is applied the AR(1) model. The application results are figured in tables 8 and 9.

**Table 8: Parameters estimates for ARIMA Model ER1**

Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
AR 1	0,9995	0,0012	819,21	0,000
Constant	0,0006335	0,0002319	2,73	0,006
Mean	1,1736	0,4297		
Number of observations: 1601				
Residuals: SS = 0,0755947 (backforecasts excluded)				
MS = 0,0000473 DF = 1599				
Modified Box-Pierce (Ljung-Box) Chi-Square statistic				
Lag	12	24	36	48
Chi-Square	8,2	13,2	22,8	32,0
DF	10	22	34	46
P-Value	0,606	0,927	0,927	0,942

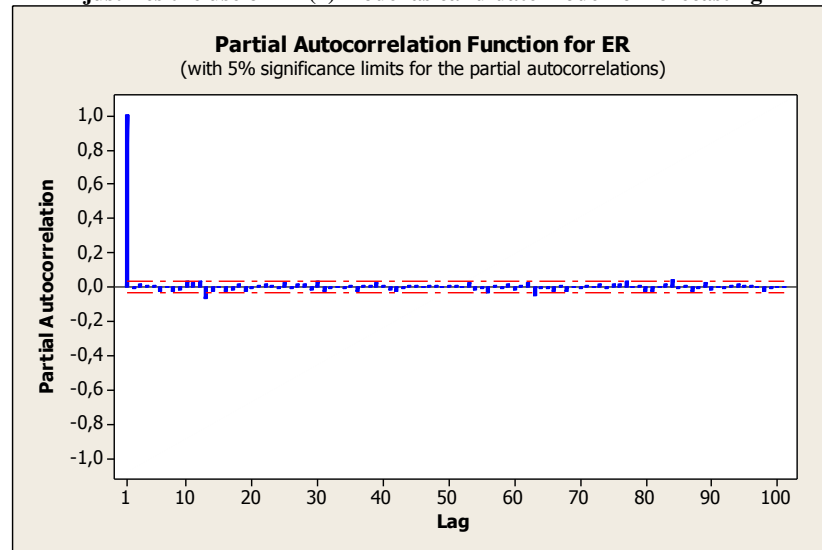
**Table 9: Parameters estimates for ARIMA Model ER2**

Estimates at each iteration				
Final Estimates of Parameters				
Type	Coef	SE Coef	T	P
AR 1	0,9968	0,0022	450,89	0,000
Constant	0,0044297	0,0002303	19,24	0,000
Mean	1,36625	0,07102		
Number of observations: 1601				
Residuals: SS = 0,132258 (backforecasts excluded)				
MS = 0,000083 DF = 1599				
Modified Box-Pierce (Ljung-Box) Chi-Square statistic				
Lag	12	24	36	48
Chi-Square	22,7	33,2	42,0	51,1
DF	10	22	34	46
P-Value	0,012	0,059	0,163	0,280

As shown in the two above tables the values of the  $\alpha$  coefficients is very close to unit (0,9995 for ER1 ; 0,9968 for ER2) indicating the same non stationarity as in the initial, non-truncated series. Any attempt to forecasting with the series before transforming it to stationary should lead to unreliable and/or trivial results. In order to demonstrate the last statement the initial series is retained up to the 3149 first observations and then demanded to give forecasts for the following 150 days, using an scheme AR(1). The legitimacy of the AR(1) model is justified by the partial autocorrelation function as shown in graph 8.

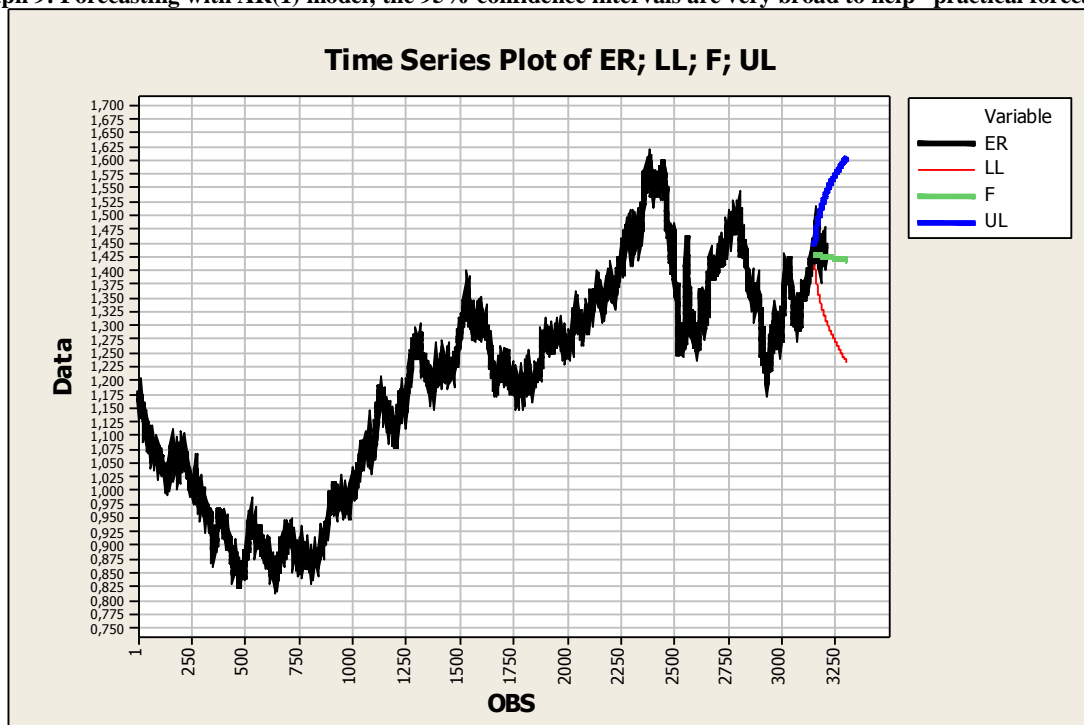
## FORECASTING WITH THE AUTOREGRESSIVE SCHEME AR(1)

**Graph 8: Partial autocorrelation function for ER. The first spike justifies the use of AR(1) model as candidate model for forecasting**



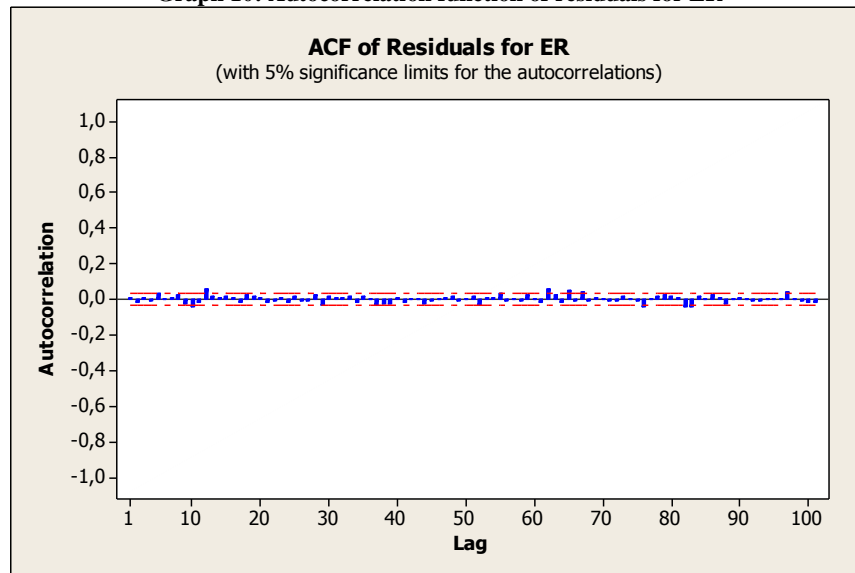
As expected, due to non stationarity of the original series the tail-truncated time series gives forecasts within so broad confidence intervals that any forecast within these intervals is practically useless. Forecasts and confidence intervals are shown in graph 9.

**Graph 9: Forecasting with AR(1) model; the 95%-confidence intervals are very broad to help practical forecasting**

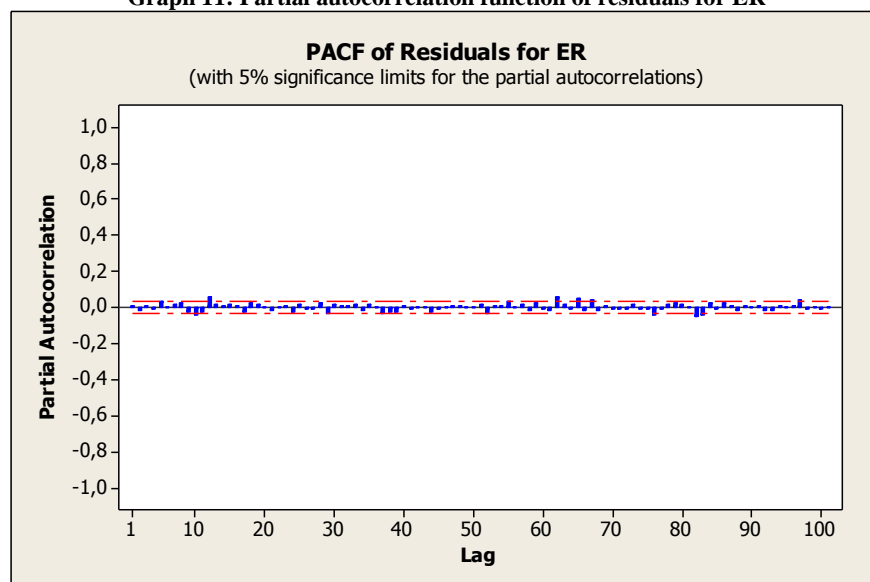


As shown in the above graph the 95%-confidence intervals are very broad to help practical forecasting. However, it is interesting that the autocorrelation function (graph 10) and the partial autocorrelation function (graph 11) of the residuals from the application of the autoregressive scheme AR(1) indicate residuals strongly resembling to white noise.

**Graph 10: Autocorrelation function of residuals for ER**



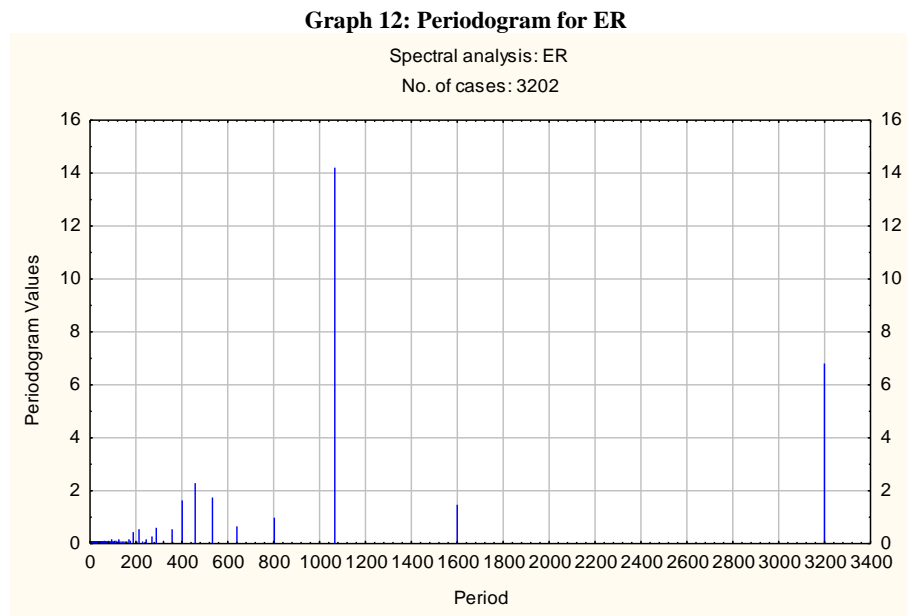
**Graph 11: Partial autocorrelation function of residuals for ER**



If the residuals form a white noise, then ER is a random walk and, therefore, by differencing ER can plausibly be expected that the first differences in ER form a white noise pattern, the distribution of which could give information on the probable changes of the exchange rate. But before attempting this direction, it is interesting to check forecasting possibilities by applying models of exponential smoothing.

## FORECASTING WITH EXPONENTIAL SMOOTHING

Given the inadequacy of the AR(1) for forecasts it will be tried the model of exponential smoothing. The periodogram for ER, graph 12, exhibits only trivial substantial periods in the series, therefore the exponential smoothing with cycles (Winters' s model) can be neglected; there will be applied on the Holt's model in its single version (no trend) and its version with trend.



In order to test the forecasting power of the exponential smoothing models, the models were applied to the first 3000 observations and demanded to give forecasts for the following 500 days.

### Forecasting with Single Exponential Smoothing

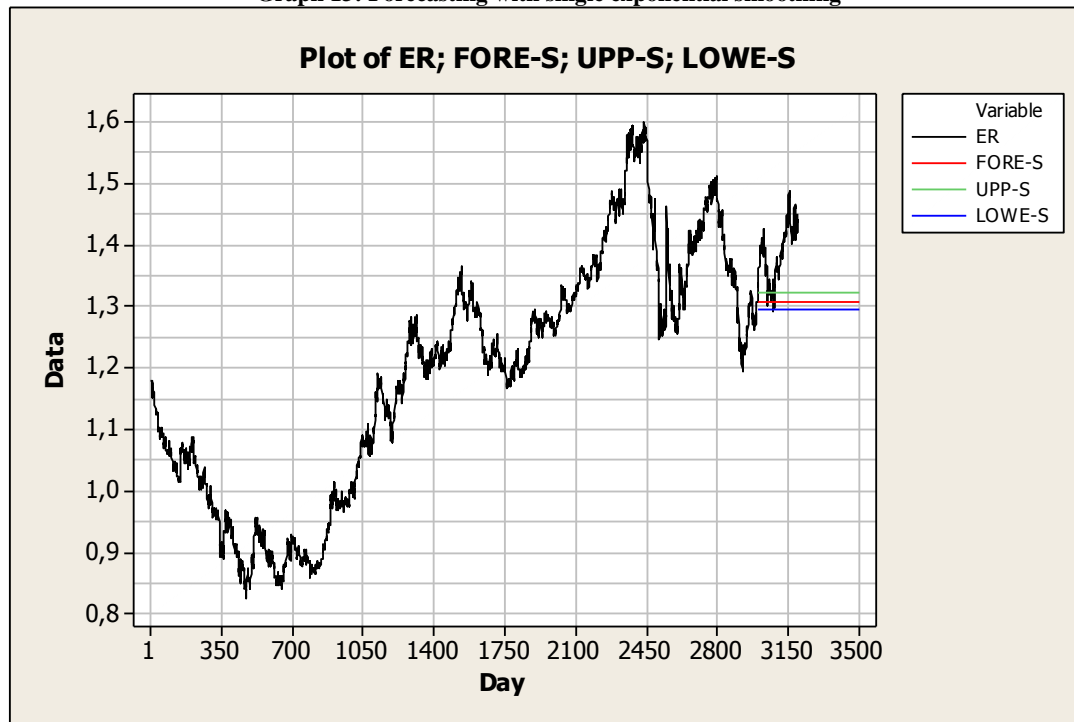
The model of single exponential smoothing is

$$F_t = \alpha X_{t-1} + (1-\alpha)F_{t-1} \quad (t=2, 3, \dots, n) \quad (4)$$

$X_t$  : the data value at time  $t$ ;  $F_t$  the forecast at time  $t$ ;  $\alpha$ : parameter ( $0 < \alpha < 1$ )

The forecasts obtained by the single exponential model are shown in graph 13

Graph 13: Forecasting with single exponential smoothing



Data ER  
 Length 3000  
 Smoothing Constant  
 Alpha 0,2  
 Accuracy Measures  
 MAPE 0,862278  
 MAD 0,010186  
 MSD 0,000179

Although the accuracy measures MAD (mean absolute deviation) and MSD (mean square deviation) indicate very satisfactory application of the model in the known range of observations, the great value of MAPE (mean absolute prediction error) exhibits failure of the model in prediction of future values. This is clearly shown in the graph in 13, which the full range of the observations (3202 observations) and the forecasts (along with confidence intervals) are overlaid.

## FORECASTING WITH DOUBLE EXPONENTIAL SMOOTHING

The model of double exponential smoothing is

$$F_t = L_{t-1} + T_{t-1} \quad (t=2, 3, \dots, n) \quad (5)$$

$$L_t = \alpha X_{t-1} + (1-\alpha)[L_{t-1} + T_{t-1}] \quad (6)$$

$$T_{t-1} = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1} \quad (7)$$

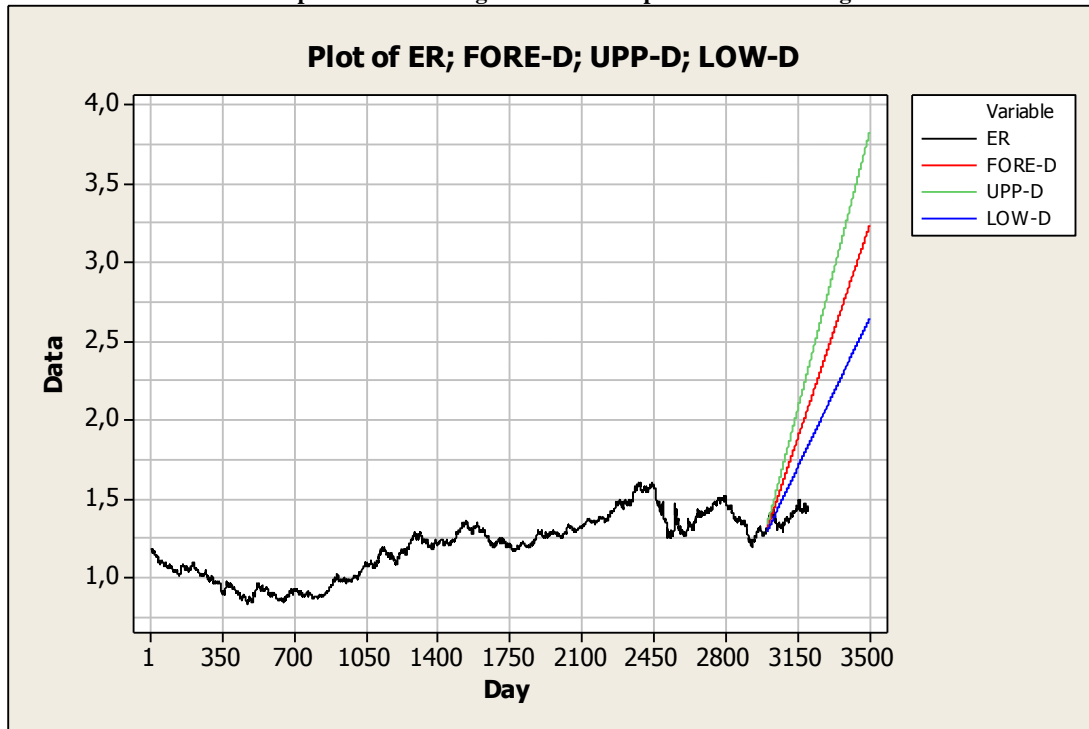
$L_t$  : the level at time  $t$ ,  $\alpha$  the weight for the level

$T_t$  : the trend at time  $t$ ,  $\gamma$  the weight for the trend

$X_t$  : the data value at time  $t$ ;  $F_t$  the forecast at time  $t$ ;  $\alpha, \gamma$ : parameters  $0 < \alpha, \gamma < 1$

The forecasts obtained by the double exponential model are shown in graph 14

Graph 14: Forecasting with double exponential smoothing



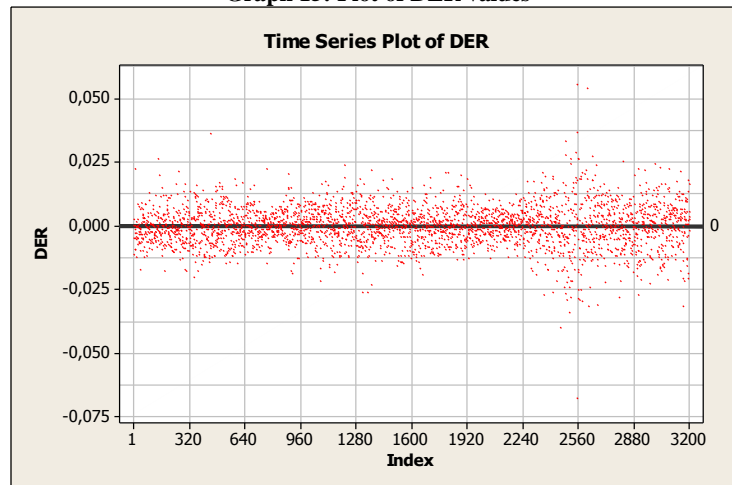
Data ER  
 Length 3000  
 Smoothing Constants  
 Alpha (level) 0,2  
 Gamma (trend) 0,2  
 Accuracy Measures  
 MAPE 0,876168  
 MAD 0,010309  
 MSD 0,000243

Again, forecasting with double exponential smoothing results to very good accuracy measures (MAD, MSD) within the known range of data, but the forecasts are systematically greater than the realized values.

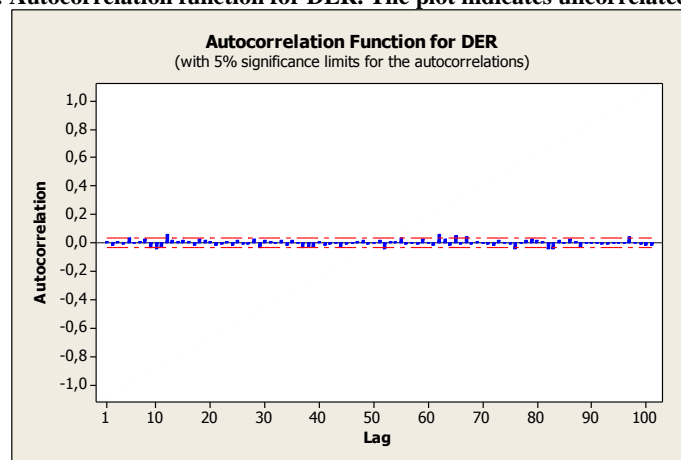
#### APPROXIMATION OF THE FIRST DIFFERENCES OF THE TIME SERIES BY LAPLACE DISTRIBUTION

Although the ARIMA and the exponential smoothing models failed to offer non trivial forecasts, the residuals from their application revealed a pattern very close to white noise. Now, given that the existence of unit root in the ER series is not rejected after the ADF test, it is worth searching the independence and the distribution of the differenced series. In graph 15 is shown the differenced series ER, where  $DER_t = ER_t - ER_{t-1}$ . The plot of the differences shows uncorrelated values, which is confirmed by the plots of autocorrelation function (graph 16) and the partial autocorrelation function (graph 17)

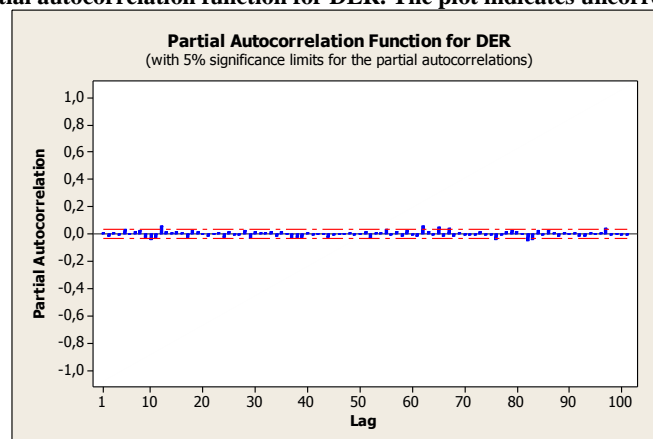
**Graph 15: Plot of DER values**



**Graph 16: Autocorrelation function for DER. The plot indicates uncorrelated differences**



**Graph 17: Partial autocorrelation function for DER. The plot indicates uncorrelated differences**



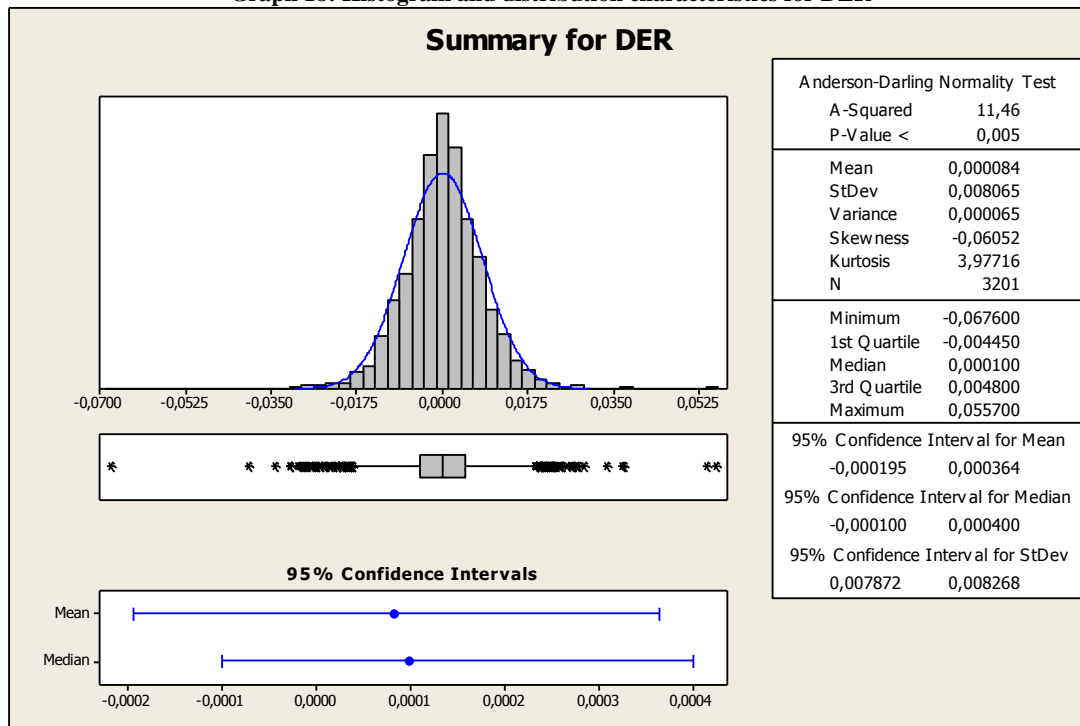
Further, the runs test for DER does not reject independence of values. The p-value of the test (0,404) is much greater than the critical value 0,05.

**Table 10: Runs Test for DER.**

Runs test for DER  
 Runs above and below K = 0,0000843174  
 The observed number of runs = 1625  
 The expected number of runs = 1601,40  
 1613 observations above K; 1588 below  
 P-value = 0,404

As shown in graph 18, the distribution of DER is highly symmetric (skewness= -0,06052, very close to zero), leptokurtic (kurtosis=3,97716>3), with mean almost zero (m=0,000084) and very small variance ( $s^2=0,000065$ ).

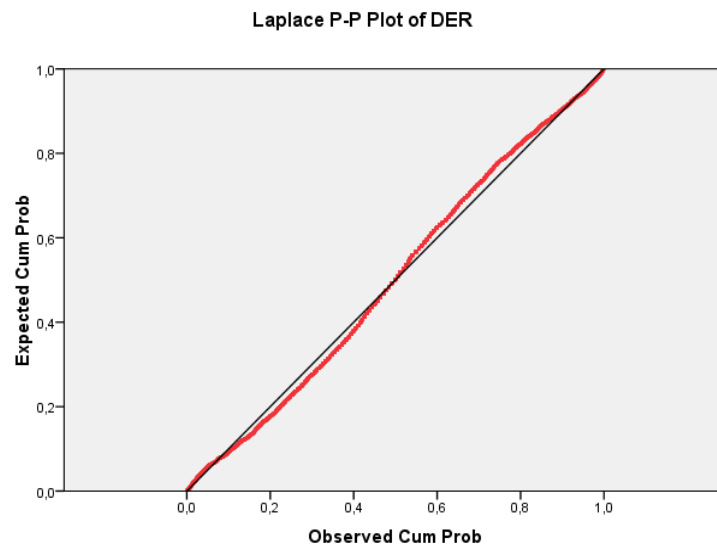
**Graph 18: Histogram and distribution characteristics for DER**



Moreover, the shape of the distribution is very close to Laplace distribution (double exponential distribution). Indeed, comparing the distribution with several theoretical distributions, it was found that the best probability distribution model describing the DER frequency distribution is the Laplace distribution. The Laplace P-P plot of DER is shown in graph 19

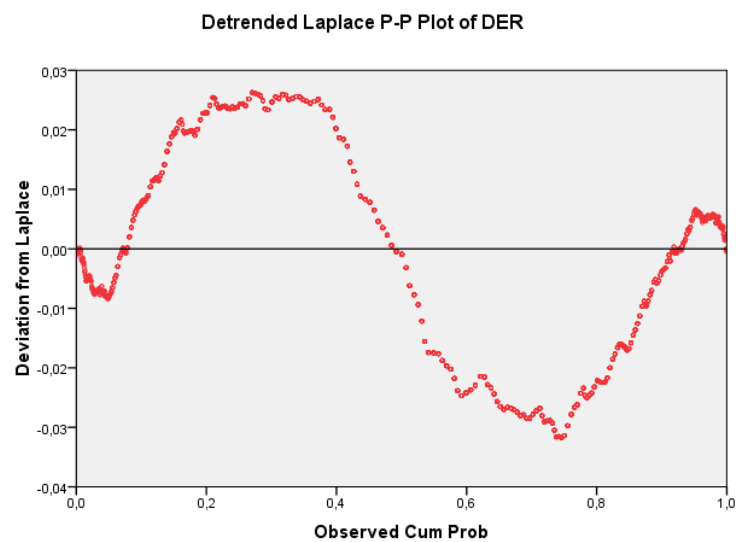


**Graph 19: Laplace P-P plot of DER. The empirical cumulative distribution function (cdf) is very close to the theoretical Laplace cdf.**



The detrended Laplace P-P plot of DER is as in graph 20

**Graph 20: Detrended Laplace P-P plot of DER**



Given the good approximation of DER distribution by the Laplace distribution, the latter can be used to calculating probability of appearance of specific values of DER.

The probability density function of Laplace distribution is

$$f(x) = (1/2b)\exp[-|x-\mu|/b] \quad (8)$$

$\alpha$ : location parameter ;  $b > 0$  scale parameter

mean= $\mu$

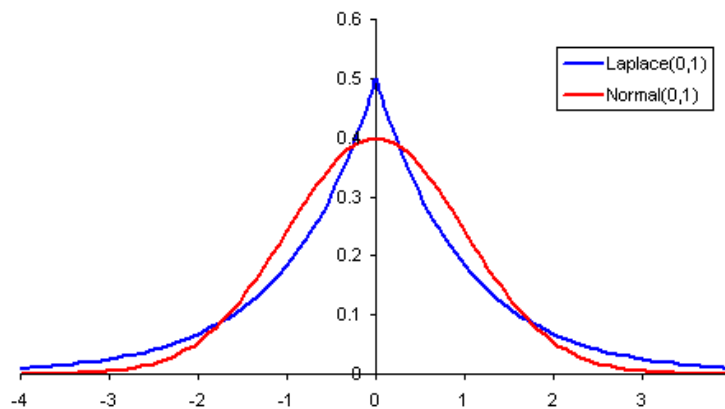
variance= $2b^2$

skewness=0

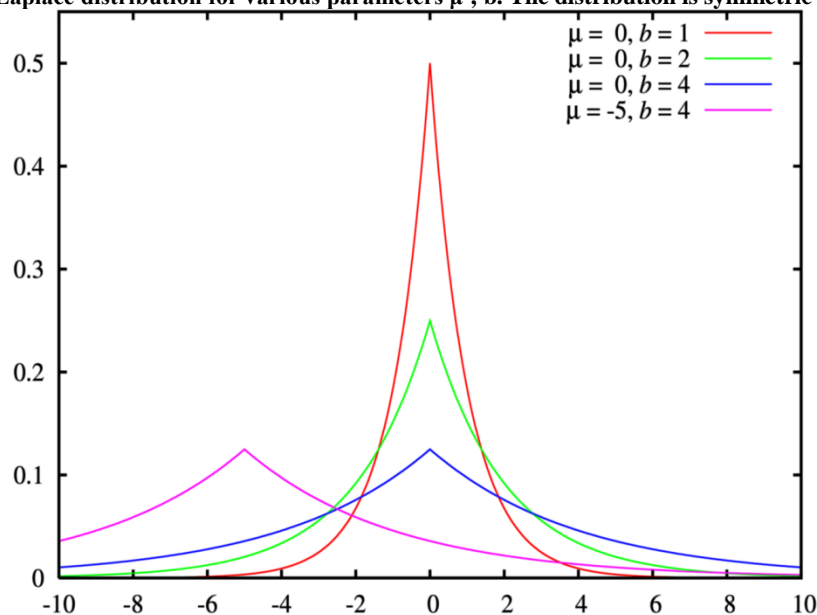
Kurtosis=6

For  $\alpha=0$  and  $b=1$ , the distribution is the standard Laplace distribution, which can be obtained as the difference between two independent exponential distributions with same parameter. Shapes of Laplace distribution for various parameters are shown in graphs 21 and 22.

**Graph 21: The standard Laplace distribution. The tails are thicker than the ones of the normal distribution**



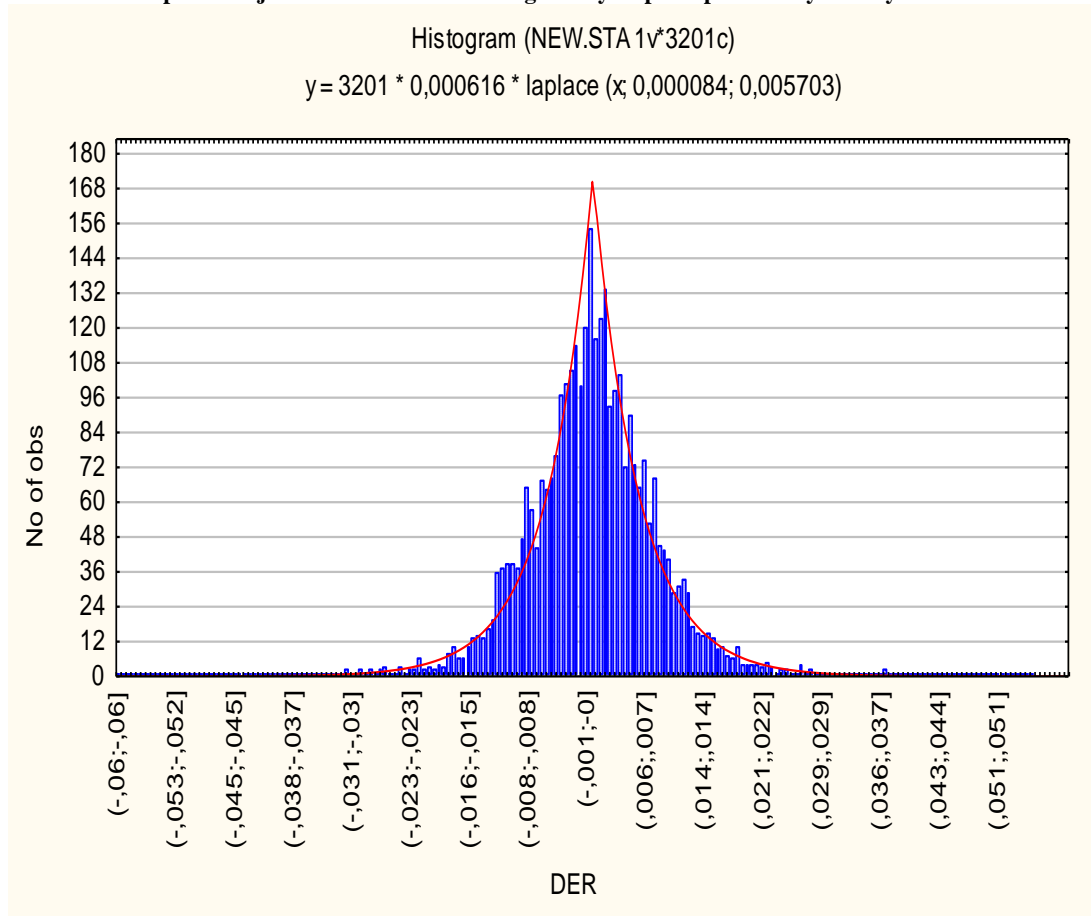
**Graph 22: Laplace distribution for various parameters  $\mu$  ;  $b$ . The distribution is symmetric to the mean.**



The adjustment of the DER histogram by Laplace probability density function is as in graph 23. The  $\mu$  parameter is 0,000084 and the  $b$  parameter is 0,005703. Therefore, the probability density function of DER is

$$f(x) = (1/2 * 0,005703) * \exp[-|x - 0,000084| / 0,005703] \quad (9)$$

**Graph23: Adjustment of the DER histogram by Laplace probability density function**



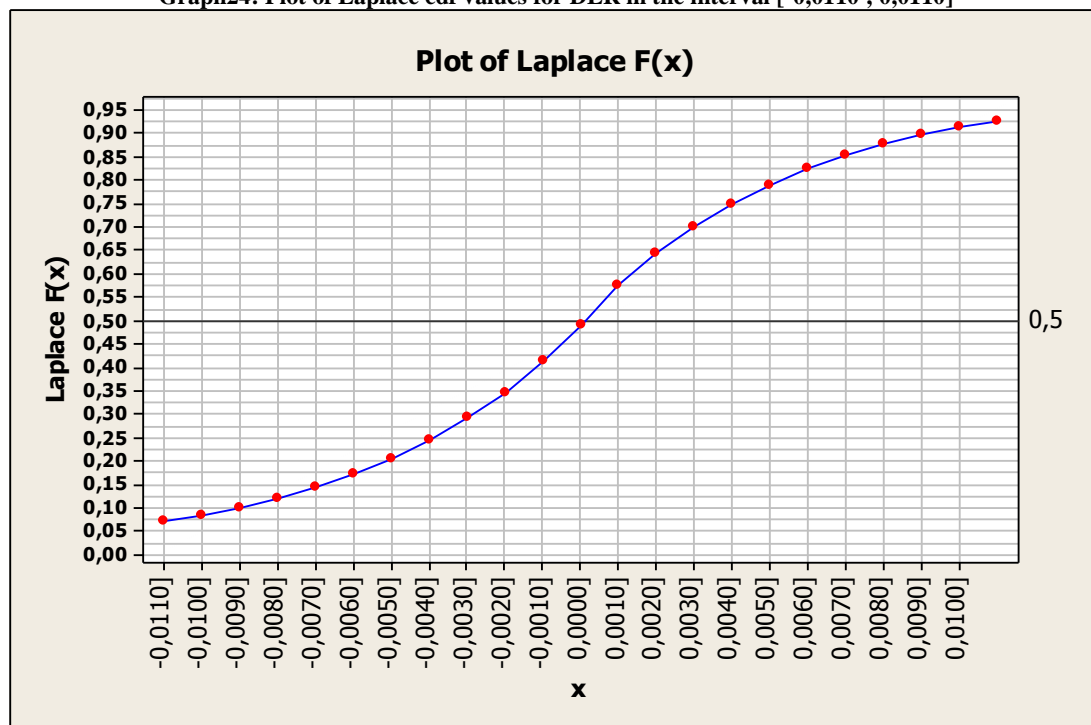
Given the PDF 9 and using the probability calculator of the software STATISTICA with the specific parameters of  $\mu$  and  $b$  one can obtain the probability of any value of DER. Table 11 shows Laplace cdf values for several values of DER and probabilities for several intervals of DER

Table 11: Laplace cdf values for several values of DER and probabilities for several interval of DER

DER up to	Laplace cdf value	DER interval	Probability for DER to lay in the interval
-0,0110]	0,0716		
-0,0100]	0,0853	[ -0,0110 ; -0,0100]	0,0137
-0,0090]	0,1017	( -0,0100 ; -0,0090]	0,0164
-0,0080]	0,1211	( -0,0090 ; -0,0080]	0,0194
-0,0070]	0,1444	( -0,0080 ; -0,0070]	0,0233
-0,0060]	0,1720	( -0,0070 ; -0,0060]	0,0276
-0,0050]	0,2050	( -0,0060 ; -0,0050]	0,0330
-0,0040]	0,2443	( -0,0050 ; -0,0040]	0,0393
-0,0030]	0,2911	( -0,0040 ; -0,0030]	0,0468
-0,0020]	0,3469	( -0,0030 ; -0,0020]	0,0558
-0,0010]	0,4134	( -0,0020 ; -0,0010]	0,0665
0,0000]	0,4923	( -0,0010 ; 0,0000]	0,0789
0,0010]	0,5742	( 0,0000 ; 0,0010]	0,0819
0,0020]	0,6427	( 0,0010 ; 0,0020]	0,0685
0,0030]	0,7001	( 0,0020 ; 0,0030]	0,0574
0,0040]	0,7484	( 0,0030 ; 0,0040]	0,0483
0,0050]	0,7883	( 0,0040 ; 0,0050]	0,0399
0,0060]	0,8228	( 0,0050 ; 0,0060]	0,0345
0,0070]	0,8513	( 0,0060 ; 0,0070]	0,0285
0,0080]	0,8752	( 0,0070 ; 0,0080]	0,0239
0,0090]	0,8952	( 0,0080 ; 0,0090]	0,0200
0,0100]	0,9121	( 0,0090 ; 0,0100]	0,0169
0,0110]	0,9263	( 0,0100 ; 0,0110]	0,0142

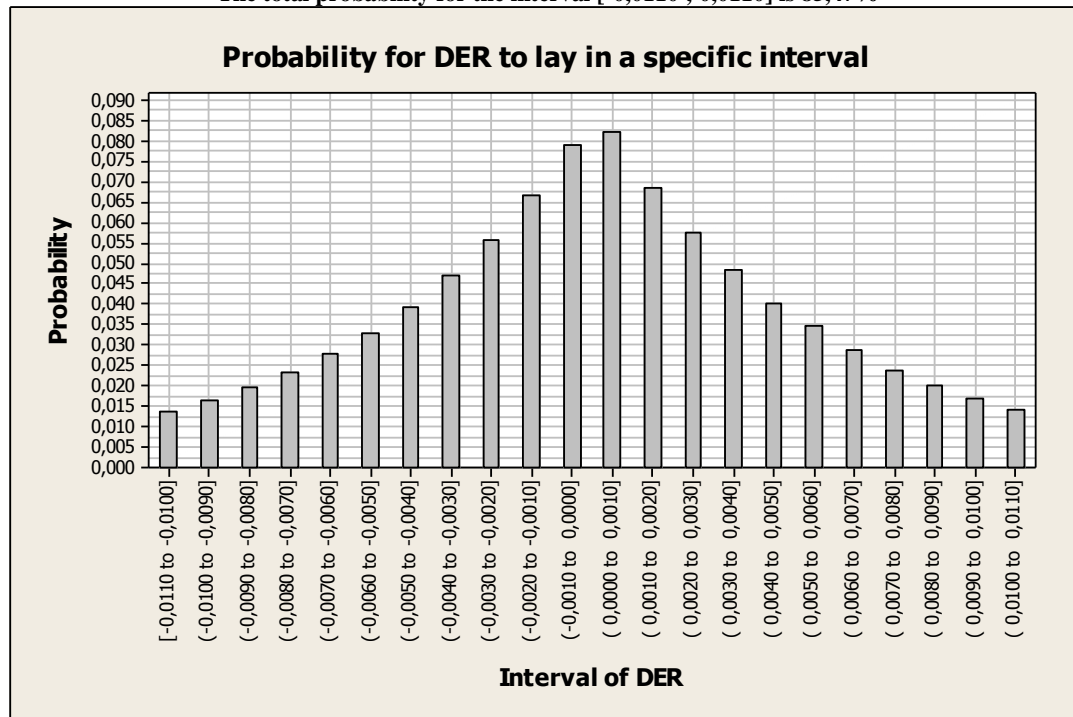
A quick tool to estimating probability for any DER in the interval [-0,0110 ; 0,0110] is offered in graph 24

Graph24: Plot of Laplace cdf values for DER in the interval [-0,0110 ; 0,0110]



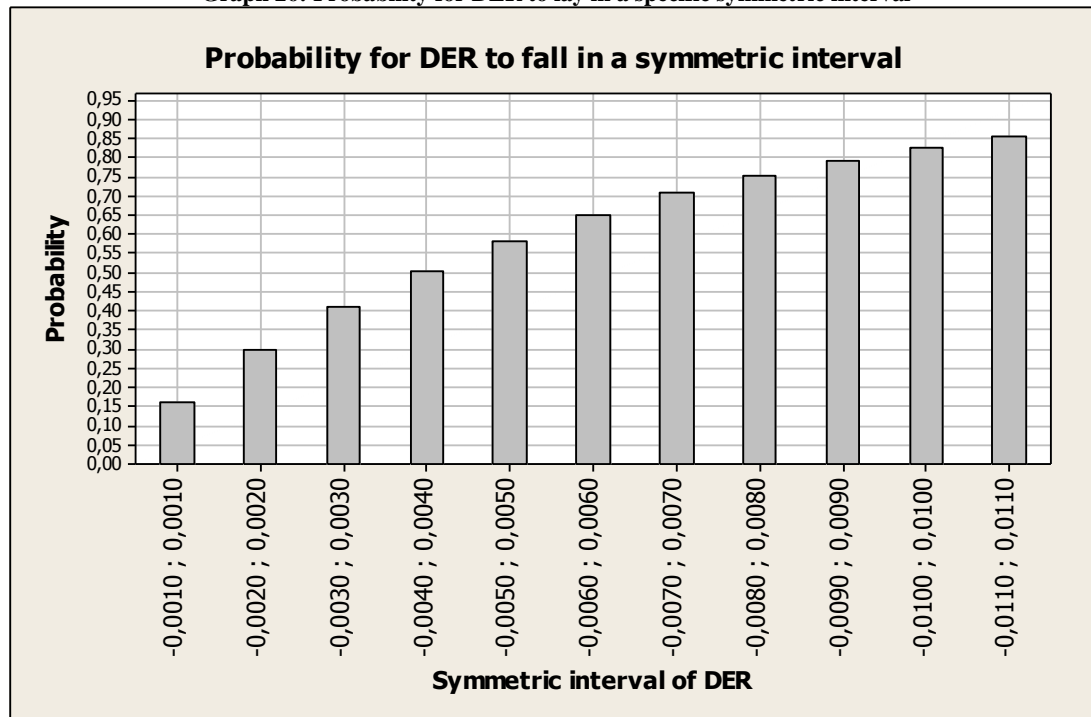
The corresponding probability DER to fall in a specific interval is shown in graph 25

Graph 25: Probability for DER to lay in a specific interval.  
The total probability for the interval [-0,0110 ; 0,0110] is 85,47%



Graph 26 shows probability for DER to lay in specific intervals, symmetric to the origin.

Graph 26: Probability for DER to lay in a specific symmetric interval



## CONCLUSIONS

The presence of unit root in the ER series failed to offer non trivial confidence intervals for forecasts of the exchange rate. Differing the ER time series resulted to white noise, which cannot be submitted to ARIMA or/and exponential smoothing forecasting techniques. However, the distribution of the differed ER gives first differences following closely the distribution Laplace. Estimating the parameters of this distribution from the data one obtains probabilities for the differences to lay in any wished interval. Further, the fact that the first differences follow the distribution Laplace and knowing that this distribution appears as difference between two independent variables, each following the exponential distribution, imposes the idea that the increases and the decreases in the exchange rate follow separately and independently the exponential distribution.

## AUTHOR INFORMATION

**Paraschos Maniatis** teaches business at Department of Business Administration at Athens University of Economics and Business, 76 Patission St., Athens, GR-104 34, E-mail: [pman@sch.gr](mailto:pman@sch.gr) and in the Kuwait-Maastricht Business School, MBA Program, Dasma-Kazima Street, P.O. Box: 9678 Salmiya, 22097 Kuwait. E-mail: [paris@kmbs.edu.kw](mailto:paris@kmbs.edu.kw)

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